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BRIEF NOTE: THOUGHTS ABOUT THE ESSENTIALS OF SIMULATION MODELLING

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Abstract—During the past few years, I have been involved, in one way or another, with developing courses on simulation methods, simulation methodology, and applications of simulation techniques to real world problems. In the course of developing and teaching such courses, a reasonable step-by-step approach to the simulation of real world systems has evolved. This paper represents an attempt to present a "kernel" on the subject and it is not offered as a definitive treatment of the subject, but rather, it is offered in the hopes of stimulating further thinking and refinement.

1. INTRODUCTION

In a recent paper, Spanier [1] discusses some essentials of mathematical modelling. His discussion aims at developing a "kernel" methodology which he elegantly portrays in Fig. 1 of his same paper. In this figure, Spanier displays a flowchart/schematic for the mathematical modelling process. This schematic points the way to a methodology for communicating the essentials of mathematical modelling to students. In the following discussion we examine essentially the same problem for simulation modelling.

2. THINKING SIMULATION

With the advent of large core, high speed computers, as well as the new generation of low cost, mid-range minisystems, simulation approaches to real world problems are now reaching full bloom. Simulation software is now generally available for all levels of computer systems and configurations, and simulation societies and journals are now coming into being.

With this in mind, we begin our discussion of a step-by-step approach to simulation modelling. Because this approach was developed for the nonscientist, we will be slightly more detailed in our discussion.

3. THE SIMULATION METHODOLOGY

In Fig. 1, the step-by-step simulation methodology is illustrated. The more mathematical readers will notice similarities between Spanier's [1] Fig. 1 and Fig. 1 in this article. This merely illustrates the optimality of the spine around which both approaches have been developed. Let us briefly discuss each of the steps in this approach.

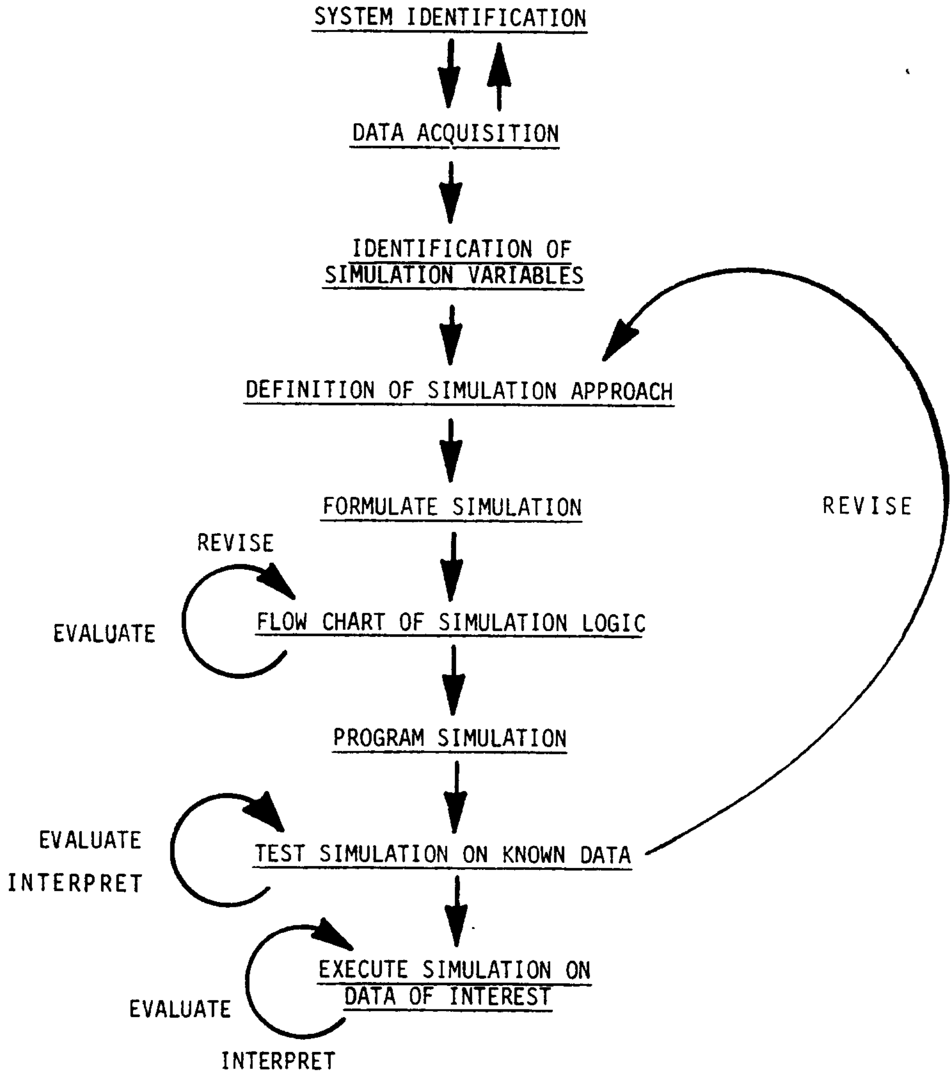

Fig. 1. Step-by-step simualtion methodology.

System identification

As simple as it may appear to be, identification of the system to be simulated is a crucial step in the development of simulation. Far too many times I have seen students try to simulate much more than was necessary. And on rare occasions, I have seen students simulate less than what was necessary. Hence, questions of oversimplification or undersimplification are of extreme importance, particularly when the results of the decision-making situation might be utilized in some type of medical therapy regimen or airport traffic planning program. One must remember that simulation involves the construction of some type of model which describes the system's operation in terms of individual events, elements, and/or components. Further refinements involve descriptions of the interrelationships between the components/elements of the simulation model. Thus, simulation is a means of dividing a model into its component parts and allowing one to investigate the results of the interactions between these parts.

Understanding how much or how little detail to place into a simulation model is one of the most difficult portions of the simulation scheme. It requires familiarity with the problem under investigation; i.e., what results are needed. It requires an understanding of the system to be simulated, hence the feedback between the data acquisition step and the system identification step in Fig. 1. Finally, it involves that elusive item known as "simulation experience." This comes only from having tried to formulate many simulations.

There is no real shortcut explanation which will tell a student how to plan a simulation which has just the right level of complexity. What we attempt to do, in our classes, is to illustrate cases involving too little or too much complexity for the output information required. Useful examples which can be made to display all levels of complexity may be found in such problems as inventory control, large harbor waiting time simulations, and airport control simulations. I have found that a canonical example of levels of simulation complexity may be found in modelling the behavior of cellular systems. Details may be found in Witten [2–4]. Depending upon what are the questions one wishes to answer, it is possible to build a very simple simulation model into one which is quite complex. If one illustrates the increase of complexity in the simulation as a function of the change in complexity/output information required by the question being put to the simulation model, then the students build up an association which allows them to see how a question requires a certain level of simulation complexity. Further, one may then take a complex simulation and show why, though it might answer a simple question, it was not necessary to go overboard when a less complex simulation would have sufficed.

Data acquisition

Once the system for study has been identified, it is important to obtain as much knowledge/data on the system as is available. This is necessary for three important reasons:

(1) Correct formulation of the simulation requires a well-balanced understanding of the real-world system and its behavior. Data acquisition will help develop this understanding. This will hopefully lead to a realistic/"correct" formulation of the simulation logic;

(2) Any simulation has parameters whose values must be somehow ascertained. Data acquisition usually yields actual values of the parameters. Or, in the case where it does not yield values, it often leads to insights as to how one might estimate those values;

(3) When it comes time to test the accuracy of the simulation, data must be available to do so. An efficient data acquisition step usually nets this necessary data. Or, it nets insights as to how to estimate the data values.

Identification of simulation variables

In this step we define our input, output, and "interstep" variables. The "interstep" variables are those variables whose calculation is necessary in order to get from the input variables to the output variables, as formulated from our system identification analysis.

Definition of simulation approach

At this point, we are ready to define the form of the simulation. In general, our lectures tend to categorize the simulation types as follows:

(a) Simulation language—such as GPSS, DYNAMO, SIMPAC, GASP, or SIMSCRIPT;

(b) Analytic—this simulation approach makes use of analytic equations which describe the dynamical behavior of the system;

(c) Monte Carlo simulation;

(d) Mixed type—this simulation approach mixes some combination of the previous three types of simulation.

Formulate simulation model

At this stage of our methodology, we begin the actual formulation of the simulation. This may be simply a block diagram showing a rough logic flow; or, it may be a diagram with the appropriate equations/rules annotated in the correct positions.

Flowchart simulation model

While it is not always necessary to flowchart a simulation logic, we emphasize the efficiency of this step; particularly to beginners in the simulation world. At this point we also have a brief discussion of flow chart symbology and logic. It is important to emphasize that this is the first step where logic errors, as well as inaccuracies in formulation and system identification, may occur and be corrected. This is why we have a revision loop at this step.

Program simulation model

This step is self-explanatory. The students are encouraged to make use of CRT terminals, batch processing, or non-CRT terminal input methods to program their simulation. Programming may be done in any number of available programming languages or simulation languages.

Test simulation or known data

The importance of this step cannot be overemphasized. We have found that the general attitude in simulation is one of "now that I've gotten the thing programmed and running, it must work correctly." Hence, we emphasize this step as a second check in our simulation methodology. Here, we use available data on the real world system as a check on the behavior of our simulation model. Excessive deviation between the two necessitates reevaluation and revision of the simulation.

Evaluate simulation on data of interest

At this point, if all has gone well, and we have a reasonable level of confidence in our simulation model, then we are set to evaluate our simulation on the data of interest.

4. CLOSING THOUGHTS

This methodology, I have just described, has been included in a number of different courses over the past two years. An expanded discussion will appear in a set of lecture notes [5], which has been developed for a graduate systems analysis course offered by the University of Southern California Department of General Systems.

In closing reflection I would like to reemphasize the fact that this discussion presents some ideas about systems modelling methodology. It is not meant to represent the final solution.

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